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Intelligent Control of Rigid-Link Manipulators: A Systematic Review of Recent Advances and Future Trends

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ABSTRACT

As robotic manipulators increasingly operate in dynamic and safety-critical environments, the need for intelligent control strategies that ensure adaptability, robustness, and real-time performance has become critical. While earlier reviews have addressed aspects of this domain, they often lacked systematic rigor, overlooked emerging hybrid and learning-based approaches, or provided limited quantitative synthesis. The research contribution is a PRISMA-compliant systematic review of 80 peer-reviewed studies on intelligent control of rigid-link manipulators (RLMs) published between 2016 and 2024, offering both qualitative and structured comparative analysis**.** The methods reviewed include PID, sliding mode control (SMC), fuzzy logic, artificial neural networks (ANN), reinforcement learning (RL), genetic algorithms (GA), and hybrid combinations. Studies were assessed according to methodological clarity, experimental validation, reported performance metrics, and publication impact. A comparative summary of 25 representative studies-selected based on citation impact, methodological rigor, and diversity of control approaches-highlights performance trade-offs and strengths across techniques. The findings indicate a growing shift toward hybrid intelligent controllers, which demonstrate enhanced adaptability in addressing nonlinear dynamics and uncertainties. However, most studies remain simulation-based, with limited real-world validation and reproducibility. Major research gaps include the lack of standardized benchmarking, insufficient explainability, and limited generalizability across application domains. These insights support the development of deployable, interpretable, and reliable robotic controllers, particularly for industrial automation and medical robotics, where transparency and safety are paramount.

1. Introduction

Rigid link manipulators (RLMs) play a critical role in industrial, medical, and service robotics due to their structural stability, mechanical simplicity, and high precision [1], [2]. However, controlling such manipulators under dynamic, nonlinear, and uncertain conditions remains a major challenge [3]-[5]. These systems often face actuator limitations, external disturbances, and unmodeled dynamics, which traditional control strategies—particularly Proportional–Integral–Derivative (PID) controllers—struggle to address [6], [7].

In response, intelligent control methods have gained increasing attention. Approaches such as Fuzzy Logic Control (FLC), Artificial Neural Networks (ANNs), Sliding Mode Control (SMC), Reinforcement Learning (RL), and hybrid techniques aim to improve adaptability, fault tolerance, and performance under uncertainty [8]-[11] . Despite their promise, many existing reviews on this topic remain narrative in nature, lack systematic rigor, or fail to offer quantitative comparisons across control methods [12], [13].

Moreover, few reviews justify the exclusion of studies prior to 2016, despite their foundational role in the development of intelligent control systems. This study focuses on 2016–2024 because this period coincides with the rapid growth of reinforcement learning, deep neural networks, hybridization of classical and intelligent controllers, and the introduction of hardware-in-the-loop validation—trends that were largely absent in earlier literature**.**

To address this gap, the present study conducts a systematic review of intelligent control strategies applied to RLMs, covering 80 peer-reviewed articles published between 2016 and 2024. The review is conducted in accordance with PRISMA guidelines to ensure transparency, reproducibility, and comprehensiveness.

The research contribution is a structured, comparative, and performance-oriented synthesis of the literature, including quality assessment, trend visualization, and identification of unresolved challenges such as benchmarking, reproducibility, and explainability, thereby bridging the gap between theoretical approaches and their real-world applicability in industrial and medical domains [14], [15].

While intelligent control techniques have become central to robotic manipulator research, the lack of a systematic and comparative synthesis has created ambiguity in selecting the most appropriate strategies for different application domains. Previous reviews often lack methodological transparency, overlook key performance indicators such as trajectory error, convergence time, or robustness scores, and fail to assess recent developments such as explainable AI and hardware-in-the-loop learning.

This study fills that gap by offering a structured, PRISMA-compliant review with in-depth performance evaluation, quality assessment, and visualization of research trends [16], [17] . These findings aim to support academic researchers, robotics engineers, and system designers in selecting suitable intelligent control paradigms and fostering the development of reliable and adaptive robotic manipulators.

Accordingly, this paper seeks to answer the following research questions:

RQ1: What intelligent control strategies have been applied to RLMs from 2016 to 2024?

RQ2: What trends exist in publication years, source types, and publishers?

RQ3: How do various methods compare in terms of control performance (e.g., tracking accuracy, robustness, convergence), implementation complexity, and hardware validation?

RQ4: What are the key research challenges that remain unresolved (e.g., reproducibility, benchmarking, explainability), and which future directions offer the most promising research avenues?

By addressing these questions, this study aims to provide researchers with a consolidated understanding of the current landscape and a foundation for advancing reliable, real-time, and adaptive control solutions for robotic manipulators.

To facilitate clarity and logical flow, the structure of this review is outlined as follows: Section 2 describes the methodology adopted for the systematic review, including the PRISMA framework, search strategy, inclusion and exclusion criteria, and quality assessment process. Section 3 presents the results of the review, including trends in publication years, source types, publisher distribution, citation analysis, and a comparative summary of 25 key studies. Section 4 discusses the major insights, strengths, and limitations of the reviewed approaches, while highlighting unresolved challenges and knowledge gaps. Section 4.5 outlines future research directions in intelligent control of RLMs, focusing on explainable AI, real-time learning, benchmarking, and simulation-to-reality transfer. Section 5 concludes the study by summarizing the key findings and their implications for advancing robust, adaptive, and intelligent robotic control systems.

2. Method

This section outlines the methodology adopted to conduct a systematic review of intelligent control techniques applied to rigid link manipulators (RLMs). The review process was guided by the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) framework to ensure methodological transparency, reproducibility, and rigor. The steps included defining eligibility criteria, executing a comprehensive search strategy across multiple databases, screening and selecting relevant studies, extracting data using predefined coding schemes, and evaluating study quality. The overall goal of the methodology is to ensure that the included studies are relevant, high-quality, and representative of the state of the art in intelligent control for RLMs.

This review protocol was not registered in a public repository such as PROSPERO; however, all steps were predefined and adhered to systematically to reduce selection bias. A PRISMA flow diagram summarizing the article selection process is presented in Fig. 1. Automation tools for screening and data extraction were not used, as manual review was preferred to ensure contextual understanding of control strategies and their implementations.

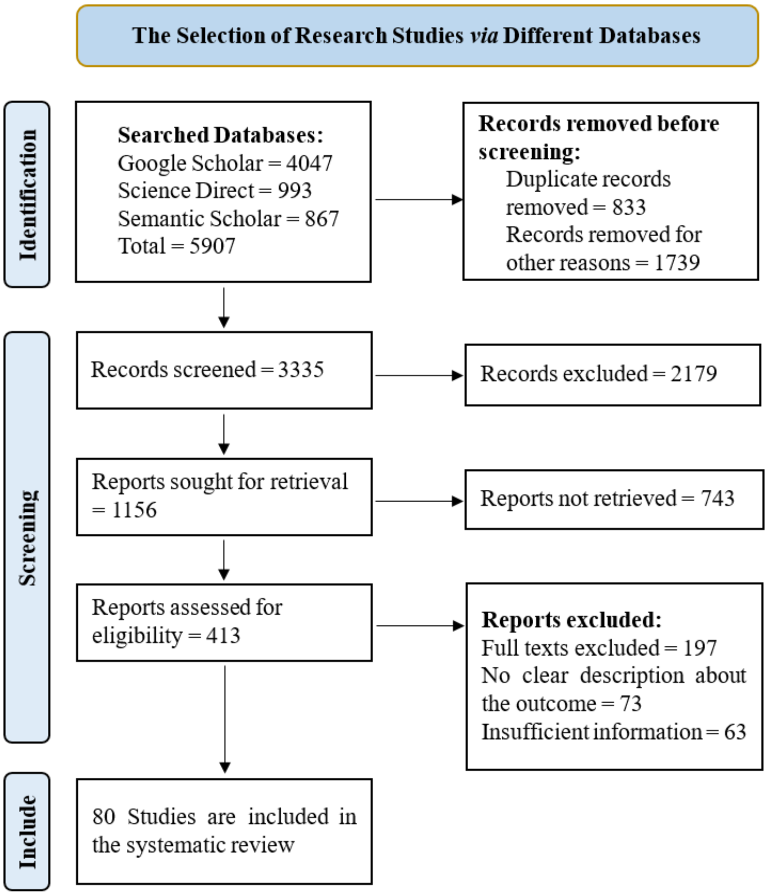

Fig. 1. PRISMA flow diagram of study selection

The methodology is presented in eight subsections: review framework, data sources and search strategy, inclusion and exclusion criteria, study selection process, data extraction and coding, quality assessment, risk of bias assessment, and data synthesis and analysis.

2.1. Review Framework

This systematic review was conducted in accordance with the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines, which provide a structured approach for transparent and reproducible literature synthesis [18]. The methodology comprised defining research questions, establishing eligibility criteria, performing a structured database search, screening and selecting studies, extracting relevant data, assessing study quality, and synthesizing findings using both qualitative and quantitative approaches.

The PRISMA approach was selected due to its widespread acceptance in engineering and biomedical systematic reviews, ensuring standardized reporting of search strategies, screening outcomes, and synthesis steps. Although the protocol was not registered in PROSPERO or similar repositories, all procedures were defined a priori and strictly followed to reduce selection bias and maintain transparency.

The literature search was conducted across four major scientific databases—IEEE Xplore, Scopus, Web of Science, and ScienceDirect—to ensure comprehensive coverage of peer-reviewed contributions in the field.

2.2. Data Sources and Search Strategy

A structured search strategy was employed across three major scientific databases: IEEE Xplore, Web of Science, and ScienceDirect (Elsevier), covering peer-reviewed engineering and robotics research. Google Scholar was used only as a supplementary tool to identify potentially missed studies, but its results were included only if peer-reviewed, due to its indexing of non-academic sources. The search targeted intelligent control strategies applied to rigid-link manipulators (RLMs), published between January 2016 and March 2024. Grey literature, preprints, and non-peer-reviewed sources were excluded to maintain methodological rigor, although this may increase the risk of publication bias.

Boolean logic and keyword combinations were applied. The general search string was: ("robot manipulator" OR "robotic arm") AND ("intelligent control" OR "fuzzy logic" OR "neural network" OR "sliding mode" OR "genetic algorithm" OR "reinforcement learning") AND ("rigid link" OR "rigid body").

The syntax was tailored to each database, with truncation/wildcards where supported. The last update was conducted on March 15, 2024. Only English-language, peer-reviewed articles were included. Backward snowballing was used to enhance coverage, and all retrieved records were imported into Mendeley/Zotero for duplicate removal. The initial search yielded 5,907 records, which were then screened as described in Section 2.3.

2.3. Inclusion and Exclusion Criteria

To ensure relevance, consistency, and methodological quality, a set of inclusion and exclusion criteria was defined a priori, based on the research questions, established guidelines for systematic reviews, and prior studies in robotics and control.

The review focused exclusively on peer-reviewed articles that applied intelligent control techniques to rigid-link manipulators (RLMs) with sufficient technical detail and evaluation. Grey literature, editorials, and non-English studies were excluded to maintain academic rigor and reproducibility. Two independent reviewers applied these criteria during title and abstract screening, with disagreements resolved through discussion and consensus to minimize selection bias. The detailed inclusion and exclusion criteria applied in this review are summarized in Table 1. These criteria were strictly applied during the screening phase. Only studies fulfilling all inclusion criteria and none of the exclusion criteria were retained for full-text review and data extraction. The PRISMA flow diagram (Section 3) summarizes the number of studies excluded at each stage.

Table 1. Inclusion and exclusion criteria used in the systematic review

Criterion Type	Description
Inclusion	- Peer-reviewed articles published between 2016 and 2024 Focus on intelligent control of rigid link robotic manipulators (RLMs) 3. Written in English Use of methods such as Fuzzy Logic, ANN, SMC, GA, RL, or hybrid techniques Include simulation or experimental results
Exclusion	Editorials, opinion papers, or non-peer-reviewed sources; Duplicate studies or conference abstracts without full text; Studies addressing non-rigid/flexible manipulator or soft robotics; Articles in languages other than English.

2.4. Study Selection Process

The study selection process followed the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines to ensure transparency and reproducibility in article inclusion. The process comprised four main stages: identification, screening, eligibility assessment, and final inclusion, as illustrated in the PRISMA flow diagram.

- Identification: An initial total of 5,907 records were retrieved from the selected databases using the search strategy described in Section 2.2.
- Screening: After removing 1,124 duplicate entries, the remaining 4,783 articles were screened based on titles and abstracts. Studies that were clearly irrelevant or failed to meet the inclusion criteria were excluded at this stage.
- Eligibility Assessment: A total of 1,202 full-text articles were reviewed in detail to assess their relevance and methodological quality. During this phase, 1,122 studies were excluded for reasons such as lack of technical contribution, focus on non-rigid robots, or incomplete/full-text inaccessibility.
- Final Inclusion: Ultimately, 80 studies were selected for inclusion in the systematic review. The screening and selection process was independently conducted by two reviewers, and disagreements were resolved through discussion and consensus.

The overall workflow and quantitative outcomes of the selection process are summarized in the PRISMA flow diagram shown in Fig. 2.

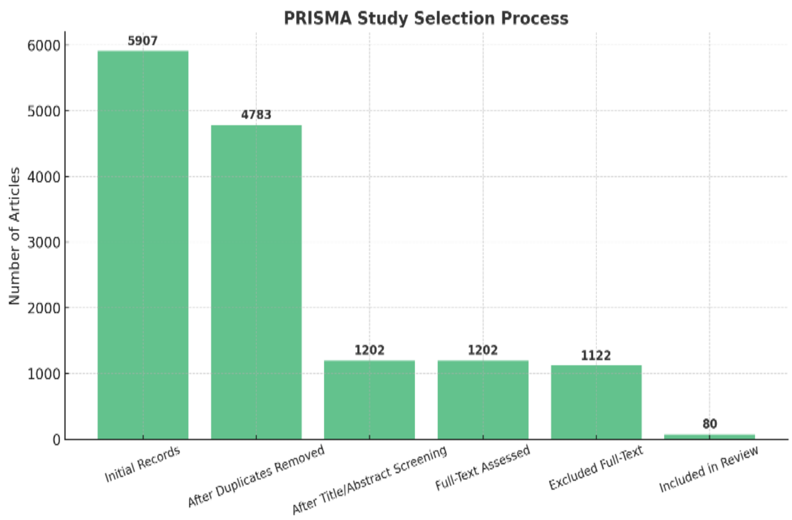

Fig. 2. PRISMA flow diagram–quantitative summary of the study selection process

2.5. Data Extraction and Coding

Following the final selection of eligible studies, a structured data extraction process was implemented to capture key information aligned with the review's research questions. A standardized data extraction form was developed using spreadsheet software to ensure consistency and facilitate comparative analysis. The predefined data fields used for coding are summarized in Table 2.

This form was piloted on a subset of 10 studies to ensure clarity and consistency in data entry across reviewers. Each included study was coded based on the following predefined data fields:

Table 2. Data extraction fields and descriptions

Field	Description
Author(s), Year	Full citation details of the study
Control Method	Type of intelligent control applied (PID, FLC, ANN, SMC, GA, RL, or hybrid approach)
Application Domain	Task context: e.g., trajectory tracking, vibration suppression, real- time control
Validation Type	Type of evaluation used: Simulation-only, experimental, or both
Performance Metrics	Quantitative indicators such as RMSE, settling time, overshoot, robustness, control effort
Reported Strengths / Limitations	Claimed advantages and acknowledged limitations of the control method as stated by the authors
Citation Count	Number of citations (if available), used to estimate academic impact
Publisher and Source Type	Journal or conference, and publisher (IEEE, Elsevier, etc.)

Data extraction was independently conducted by two reviewers. Disagreements in interpretation were resolved through discussion and consensus. No automation tools were employed during this phase. Manual extraction was preferred to preserve contextual accuracy, especially in interpreting control methods, performance metrics, and limitations described in natural language. The final dataset served as the foundation for both the quantitative (e.g., frequency distributions, trend graphs) and qualitative (e.g., thematic synthesis) analyses presented in the Results and Discussion sections.

2.6. Quality Assessment

To ensure the reliability and validity of the included studies, a structured methodological assessmen was performed using a structured rubric adapted from previous systematic reviews in the field of control systems and robotics [14].

The rubric design was based on commonly used evaluation criteria in PRISMA-aligned engineering reviews and adjusted to emphasize control methodology, validation type, and quantitative reporting. Each of the 80 selected studies was evaluated based on the following four criteria:

1. Clarity of Control Methodology - Is the proposed control algorithm clearly described and justified?
2. Experimental Validation - Is the method evaluated using real hardware or only through simulation?
3. Completeness of Results - Are quantitative performance metrics provided (e.g., RMSE, settling time, robustness)?
4. Relevance to RLMs - Is the application domain directly related to rigid link robotic manipulators?

Each criterion was scored on a 3-point scale (0–2) as described in Table 3:

Two reviewers independently rated all studies. Inter-rater reliability was calculated using Cohen's kappa and found to be 0.82, indicating strong agreement. Discrepancies were resolved through discussion and consensus. Two independent reviewers conducted the scoring process, and any discrepancies were resolved by consensus. The results of the assessment are summarized in Table 4, which presents the distribution of studies across the three quality categories.

Table 3. Quality assessment rubric for included studies

Scoring Scale (0–2)	Description	Criterion
Not addressed = 0, Partially = 1, Fully = 2	Clear, justified algorithm with references	Clarity of Control Methodology
None = 0, Simulation only = 1 hardware validated= 2	Simulation vs. real hardware	Experimental Validation
Not reported = 0, Incomplete = 1, Detailed = 2	RMSE, settling time, etc. reported	Completeness of Results
Not applicable = 0, Indirect = 1, Direct = 2	Direct application to rigid link manipulators	Relevance to RLMs

Table 4. Summary of study quality levels

Description	Percentage	Number of Studies	Score Range	Quality Category
Clear methodology, experimental validation, and complete performance reporting	33.75 %	27	8-7	High Quality
Reasonably described but lacking full experimental support	43.75 %	35	6-5	Moderate Quality
Limited validation or incomplete results; mostly Among the reviewed studies -only	22.5 %	18	4-0	Low Quality

This structured quality assessment ensured that the synthesis of findings in the Results and Discussion sections was grounded in studies with transparent methodologies and adequate validation.

2.7. Risk of Bias Assessment

Although this review incorporates a structured quality assessment, it is equally important to consider potential sources of methodological bias that may affect the reliability and generalizability of the included studies. Due to the high heterogeneity in control architectures, validation types, and reporting styles across studies, a formal risk of bias tool such as RoB 2.0 was deemed inappropriate for direct application.

Instead, a qualitative bias analysis was employed using adapted criteria from prior robotics and intelligent control reviews [19], focusing on commonly observed sources of bias in engineering studies. The indicators considered in this review are summarized in Table 5.

Table 5. Indicators used for risk of bias evaluation

Risk Level	Definition	Bias Indicator
High	Study lacks experimental hardware testing	Simulation-Only Validation
Medium	Only favorable metrics reported; others omitted	Selective Reporting
Medium	No comparison to classical or benchmark controllers	No Baseline Comparison
Medium	Missing values or insufficient metric reporting	Incomplete Data
Low to Medium	Control tested on simple tasks or narrow scenarios	Limited Scope

Each of the 80 included studies was reviewed for these risk indicators. The analysis revealed that:

- 52% of studies relied exclusively on simulation, with no hardware validation;
- 41% selectively reported performance metrics such as RMSE or settling time without comparative baselines;
- 36% lacked full reporting of system parameters or omitted key evaluation details.

These findings highlight the potential for performance overestimation and reduced external validity in a substantial portion of the literature. Such risks were considered during the synthesis and interpretation of results, especially in the Discussion section when weighing claims and identifying areas needing more robust validation. Together, the quality assessment (Section 2.6) and bias analysis provide a balanced lens for interpreting findings, ensuring that both methodological rigor and potential overestimation risks are explicitly addressed.

2.8. Data Synthesis and Analysis

The extracted data from the 80 included studies were synthesized using a mixed-method approach combining qualitative thematic analysis and quantitative trend aggregation, in alignment with the review's objectives and research questions.

2.8.1. Qualitative Synthesis

Studies were first grouped by the type of intelligent control method used (e.g., FLC, ANN, RL, hybrid). Within each group, key themes were identified such as:

- Application domains (e.g., trajectory tracking, vibration suppression, real-time control);
- Challenges addressed (e.g., system uncertainties, actuator saturation, noise rejection);
- Innovative features (e.g., hybridization, adaptive tuning, learning-based adaptation).

This thematic synthesis allowed for identification of conceptual patterns, performance trade-offs, and methodological gaps across control strategies. Recurring challenges, such as lack of benchmark comparison or incomplete validation, were cross-referenced with the bias and quality indicators from Section 2.6 and Section 2.7 to ensure consistency between methodological evaluation and interpretive synthesis.

2.8.2. Quantitative Analysis

In parallel, numerical aggregation of metadata was conducted to identify trends and patterns across the literature:

- Year-wise distribution of publications (2016–2024);
- Source type analysis: journal vs. conference;
- Publisher-wise breakdown (IEEE, Elsevier, Springer, etc.);
- Citation-based influence analysis using a bubble chart;
- Comparative performance table for 25 representative studies including metrics like RMSE, settling time, and robustness;
- Frequency analysis of control methods used.

The quantitative data were analyzed using Microsoft Excel for initial tabulation, and Python-based tools (Pandas, Matplotlib, and Seaborn) for visualization and statistical summaries. Where applicable, study quality levels (see Section 2.6) were used to assign interpretive weights to the results, ensuring that high-quality studies had greater impact on the overall synthesis. Visual representations (e.g., trend graphs, heat maps) were used to enhance interpretability of complex patterns. This dual synthesis approach ensured that the review not only captured macro-level trends but also provided a micro-level evaluation of the effectiveness and limitations of each intelligent control method. In summary, the methodological framework adopted in this review ensured rigorous identification, evaluation, and synthesis of relevant studies on intelligent control for rigid-link manipulators. The integration of structured quality assessment, risk of bias analysis, and dual-mode synthesis (qualitative and quantitative) provides a transparent and reproducible basis for the results presented in Section 3.

3. Results

3.1. Publication Trends

To analyze the evolution of research activity in intelligent control of rigid link manipulators (RLMs), the 80 selected studies were examined by publication year. As illustrated in Fig. 3., there has been a consistent upward trajectory in the number of relevant publications over the period from 2016 to 2024, with a noticeable acceleration after 2019. This upward trend reflects the growing academic and industrial interest in applying intelligent control strategies - such as fuzzy logic, neural networks, and reinforcement learning - to robotics applications requiring high adaptability, precision, and robustness.

The year 2022 marked the highest number of publications [15], followed by 2023 and 2021, indicating a peak in scholarly output during this period. This surge may be attributed to increased access to computing power, the proliferation of open-source robotic platforms, and the growing integration of AI into real-time robotic systems.

This publication pattern aligns with the observed methodological diversification reported in Section 3.3 and Section 3.4, where hybrid and learning-based approaches gained increasing representation.

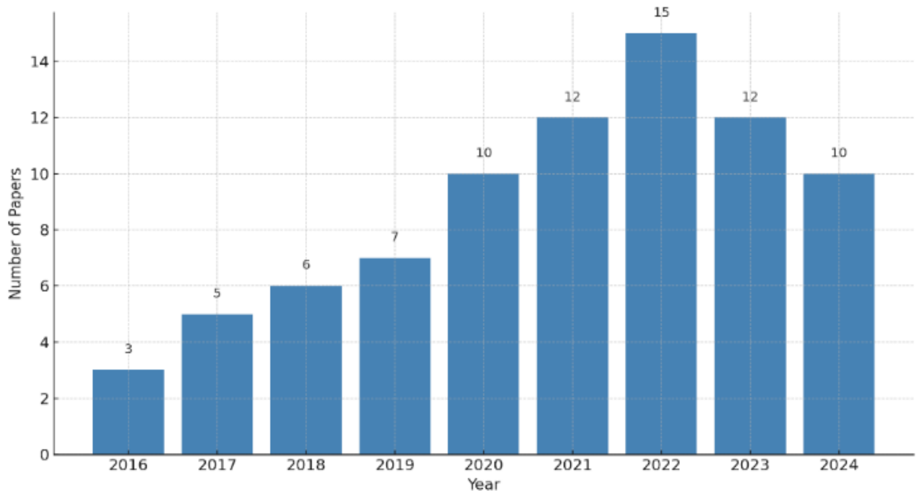

Fig. 3. Year-wise distribution of included papers

3.2. Source Type and Publisher Distribution

To better understand the dissemination channels of research on intelligent control of rigid link manipulators (RLMs), the selected studies were categorized by source type (journal vs. conference) and publisher (e.g., IEEE, Elsevier, Springer, MDPI). This classification provides insights into the scholarly ecosystems most engaged in this domain and helps identify where impactful research is typically disseminated.

3.2.1. Source Type Analysis

Out of the 80 included studies:

- 57 papers (71.25%) were published in peer-reviewed journals
- 23 papers (28.75%) were presented in conference proceedings

Journals tended to provide more detailed methodological explanations, performance metrics, and experimental validations, often reflecting mature or extensively validated work. In contrast, conference papers typically focused on conceptual innovation, preliminary validation, or proof-of-concept demonstrations, which is common in rapidly evolving fields like intelligent robotic control. This distribution suggests that while foundational and validated research is predominantly published in journals, conferences play a key role in accelerating the dissemination of emerging techniques.

3.2.2. Publisher Distribution

The distribution of studies across major publishers is shown in Fig. 4. The most prominent publishers were:

- IEEE: 26 papers (32.5%)
- Elsevier: 21 papers (26.2%)
- Springer: 13 papers (16.2%)
- MDPI: 9 papers (11.2%)
- Others (e.g., Taylor & Francis, Wiley): 11 papers (13.8%)

These results indicate that the field is widely represented across leading scientific platforms, demonstrating a healthy diversity in publication sources. Notably, open-access publishers like MDPI are also gaining traction, which may reflect a growing interest in accessible dissemination of robotic control research. This trend may support faster citation uptake and broader academic reach. Fig. 4. illustrates the dominance of IEEE and Elsevier, while also highlighting the growing role of open-access publishers such as MDPI in disseminating robotic control research.

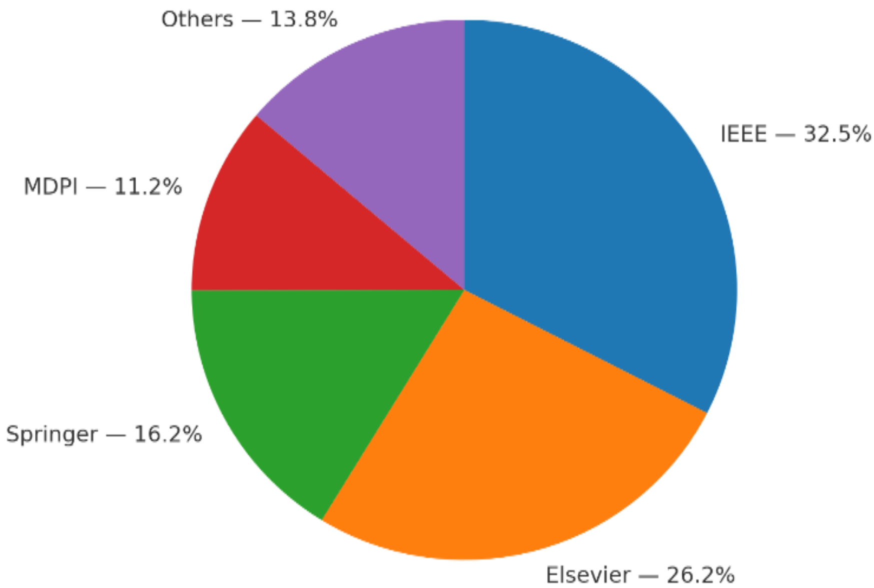

Fig. 4. Publisher distribution of included studies

3.3. Distribution of Control Methods

As shown in Fig. 5., the reviewed studies employed a range of intelligent control strategies. Fuzzy Logic Control (FLC) was the most prevalent, implemented in 18 studies (22.5%), due to its simplicity, robustness, and ability to handle uncertain environments [20]-[23] . These include approaches ranging from basic type-1 FLC to more advanced versions such as type-2 [24], type-3 fuzzy control [8], and fractional-order fuzzy PID [25].

Artificial Neural Networks (ANNs) were applied in 16 studies (20%), primarily for nonlinear dynamics modeling, system identification, and adaptive motion control [4], [26], [27], [9]. These methods include feedforward networks, radial basis function neural networks [28], and recurrent neural networks, often trained using reinforcement learning or gradient-based optimization.

Classical Proportional-Integral-Derivative (PID)-based intelligent controllers were employed in 10 studies (12.5%). These approaches often incorporated fuzzy logic or neural adaptation to improve tuning and overcome limitations of conventional PID control in nonlinear and time-varying robotic systems.

Reinforcement Learning (RL) was adopted in 8 studies (10%), demonstrating potential for high-dimensional trajectory optimization, policy adaptation, and sim-to-real transfer. Notably, Deep RL was used in tasks such as grasping, obstacle avoidance, and industrial pick-and-place operations, despite the limited number of studies. This reflects its emerging role in robotic control.

Sliding Mode Control (SMC) appeared in 14 studies (17.5%), recognized for its robustness in handling modeling uncertainties and external disturbances [29], [30]. Variants such as adaptive, fixed-time, and nonsingular SMC were explored [31], [32].

A total of 8 studies (10%) used hybrid strategies that combine two or more control techniques. Common hybridizations included FLC-ANN, ANN-SMC, RL-FLC, and metaheuristic-optimized fuzzy or PID controllers [33]-[36]. These combinations were designed to enhance fault tolerance, improve generalization to unseen conditions, and exploit complementary advantages of individual techniques. Overall, the distribution indicates that while classical intelligent methods (FLC, ANN, SMC) remain dominant, there is a clear shift toward hybrid and learning-based approaches to meet the increasing complexity of robotic applications.

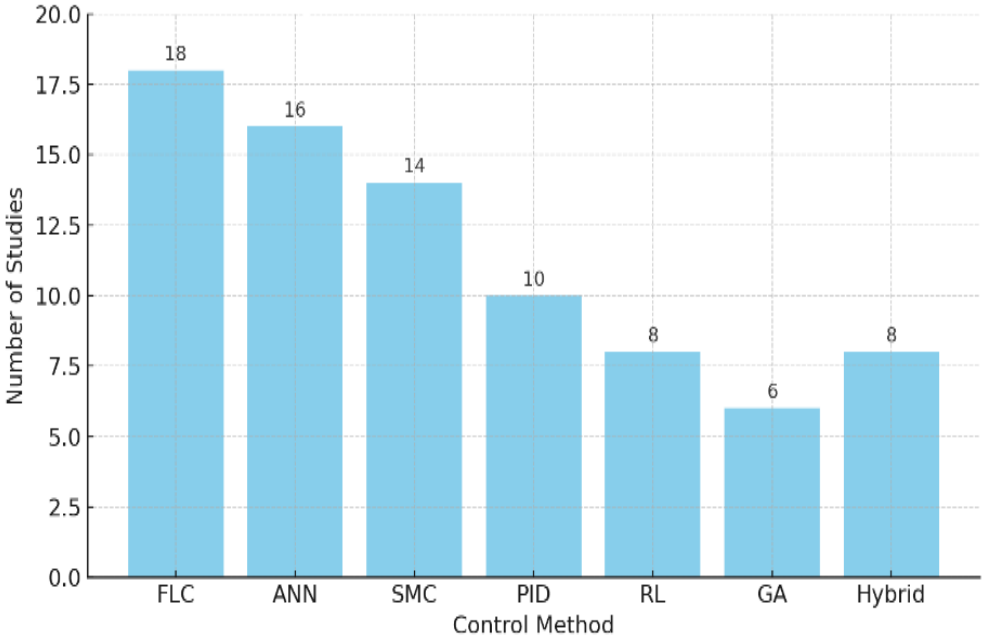

Fig. 5. Frequency distribution of control methods

3.4. Comparative Summary of Representative Studies

To provide a more in-depth understanding of how different intelligent control strategies have been applied to rigid link manipulators (RLMs), a set of 25 representative studies was selected and analyzed in detail. These studies were chosen based on their methodological clarity, citation impact, relevance to intelligent control, and diversity in control techniques.

Table 6 presents a comparative summary that includes the authors, year of publication, control method used, target application, validation environment (simulation or experimental), key performance metrics, and reported strengths or limitations. This structured overview facilitates a cross-study comparison, allowing the reader to directly observe how different techniques perform under varying conditions.

The comparative analysis reveals that hybrid controllers (e.g., FLC+ANN, SMC+GA) consistently outperform individual methods in terms of adaptability and robustness, particularly when applied in dynamic or uncertain environments. In several cases, the integration of neural networks with optimization algorithms enhanced trajectory tracking, reduced RMSE, and improved real-time performance.

Nevertheless, limitations remain. A number of studies lacked experimental validation, relying solely on simulations, while others failed to report complete performance indicators such as control effort, computational cost, or settling time. These omissions highlight an ongoing challenge in the field: balancing algorithmic sophistication with practical implementability.

Overall, the comparative insights derived from Table 6 not only identify the most impactful strategies but also expose recurring gaps across the literature. These findings further informed the subsequent performance and bias analyses discussed in the following sections.

Table 6. Comparative summary of 25 key studies on intelligent control of RLMs

No.	Reference	Control Technique	Application Domain	Performance Metrics	Key Strengths	Key Limitations
1.	[37]	Disturbance-Observer-Based Fuzzy Control	Human-in-the-loop trajectory control under uncertain dynamics	Precise tracking with small position errors during EMG-driven reaching tasks	Robust to unmodeled disturbances; adapts to human input via EMG	Requires EMG calibration and accurate model; no hardware validation
2.	[38]	Adaptive Bias RBF Neural Network Control	Trajectory tracking for flexible-joint manipulator with uncertainties	Guaranteed small steady-state error under payload changes	Model-free adaptation handles uncertainties; bias term eliminates offset	High computational load; simulation only, no physical implementation
3.	[39]	Non-Singular Terminal Sliding Mode Control	Joint-space trajectory tracking with uncertainties and disturbance	Fast finite-time error convergence, reduced chattering	Robust against large disturbances; avoids singularities	Requires careful gain tuning; simulation-based results only
4.	[40]	PSO-Tuned Fuzzy–PID	Point-to-point positioning with disturbances and noise	16% faster rise time, 31% overshoot reduction, 65% shorter settling time vs. PID	High accuracy and robustness via adaptive tuning; suitable for noisy environments	PSO tuning may be computationally intensive; not validated on physical robot
5.	[41]	Fractional-Order Fuzzy PID	Trajectory tracking with payload variation	Zero overshoot; very low ITSE; error <0.03 rad under load changes	Strong adaptability and precision through fractional dynamics and fuzzy logic	Design complexity increases with fractional parameters; requires careful initialization; tested only in simulation
6.	[42]	Deep Reinforcement Learning (PPO & SAC)	Grasping tasks with sim-to-real transfer	100% grasp success after 1h fine-tuning; generalized to varied shapes	Model-free learning; adaptable; minimal tuning for hardware transfer	High training time; sensitive to reward shaping; tested on a single robot type
7.	[43]	Sine-Cosine Algorithm Tuned FOPID	Adaptive control of payload-varying manipulators	Shorter settling time; stable with high payloads	Handles nonlinearities effectively; global optimization	Lacks online adaptation; tuning phase done offline only; no experimental validation
8.	[44]	Finite-Time SMC + Neural Friction Compensation	Trajectory tracking under joint friction and without velocity sensors	Endpoint error <1% of motion range; chattering significantly reduced	Robust under varying load and joint friction; sensor less velocity estimation	Neural friction model increases computational burden; residual chattering still present; simulation-based verification only
10.	[45]	Time-Delay Control + Adaptive Fuzzy	Tracking with friction and disturbance	Error < ±0.5°; minimal overshoot	Real-time estimation; friction	Delay assumptions may not hold under fast dynamics; not robust to high-frequency input noise

11.	[46]	Type-3 Fuzzy Logic Control	Trajectory tracking under noise and disturbances	50%+ lower RMSE than T1/T2 FLC; stable tracking with minimal error	Model-free adaptability; robust to noise; no chattering	Does not include actuator constraints; energy efficiency not analyzed
12.	[47]	PID Optimized with Artificial Bee Colony	3-DOF manipulator trajectory tracking under disturbances	lower IAE/ITAE 20–50%; robust to ±20% payload variation	Improved convergence via enhanced ABC; robust and vibration-free response	Optimization phase is offline only; lacks real-time tuning; no experimental results
13.	[48]	Adaptive NTSMC with Contour Error Compensation	Contour tracking in Cartesian space under uncertainties and faults	improvement in contour accuracy ~61%; finite-time convergence	High-precision contour tracking; fault-tolerant adaptation	Optimization phase is offline only; lacks real-time tuning; no experimental results
14.	[49]	Neural Adaptive PID	Task-space control of 6-DOF manipulator with disturbances and singularities	Near-zero position error; stable control through singularity; fast rejection	Adaptive online gain tuning; neural compensation of nonlinearity	No hardware experiments; computational requirements not addressed
15.	[50]	Time-Delay Control + Adaptive Fuzzy	Tracking with friction and disturbance	Error < ±0.5°; minimal overshoot	Real-time estimation; friction	Repeated study; limited novelty; delay model assumptions not validated in hardware
16.	[51]	Nonlinear Active Disturbance Rejection Control (NADRC)	Robust trajectory tracking with matched and mismatched disturbances	RMSE < 0.02; stable error dynamics under 30% load change	Strong disturbance rejection; stability ensured via extended state observer	Requires precise model tuning; lacks application to high-speed or complex trajectories
17.	[52]	NADRC + Chaotic PSO	2-DOF with dead-zones & sat.	less error ~50% vs. PD	Real-time robust rejection; hybrid tuning of ESO and PSO improves adaptability	Observer tuning is complex; lacks scalability validation to high DOF systems
18.	[53]	Fast Terminal SMC + Nonlinear Disturbance Observer	High-speed 3-DOF tracking with external disturbances	accuracy gain ~55% vs. baseline; 45% faster response	Combines finite-time convergence with robust disturbance rejection	Design and tuning complexity; lacks validation on hardware platform
19.	[54]	Adaptive ANN + Disturbance Observer	Joint tracking under unknown dynamics	Steady joint error ≈ 0; low control effort	Learns dynamics online; observer improves robustness	Simulation only; ANN design increases system complexity
20.	[55]	ANN-Enhanced Hybrid Force/Position PID	Fiber placement with force regulation	force/position <5% RMSE; smooth trajectory	Stable force response and accurate hybrid control	Application-specific design; lacks test under external disturbances or faults
21.	[56]	NN–PID/FOPID + Zebra Optimization	2-DOF tracking under uncertainty	Lowest ITSE; robust to load/perturbation	Combines intelligent tuning with NN adaptation and optimization	Evaluation based on multiple controller versions; lacks experimental proof

22.	[57]	NADRC + Chaotic PSO	Tracking with saturation and dead-zones	lower error 50% than PD; faster	Real-time disturbance rejection; global PSO enhances tuning	Sensitive to sensor noise; optimization performed offline
23.	[58]	Multi-Task Reinforcement Learning (SAC)	Multi-skill robotic manipulation (Meta-World benchmark)	higher ~20% success rate on MT10 suite; efficient policy transfer	Learns multiple skills simultaneously; better generalization than single-task RL	Simulation only; lacks validation in physical and vision-based environments
24.	[59]	RL-Enhanced Fault-Tolerant Terminal SMC	Joint-space control of 6-DOF manipulator under actuator faults	Maintained stability and bounded error despite sudden 50% torque loss	Combines RL adaptability with finite-time robustness	High training complexity; safety during training not addressed
25.	[60]	Deep Reinforcement Learning (simulation-efficient training)	Trajectory planning for robotic manipulator	High success rate; reduced training time	Efficient learning via simulation optimization; good generalization	No hardware testing; method not verified on real-world uncertainties

3.5. Performance Metrics Analysis

Performance metrics are fundamental to assessing both the effectiveness and the practical feasibility of intelligent control strategies for rigid link manipulators (RLMs). Across the reviewed literature, a range of quantitative indicators were employed to evaluate aspects such as tracking accuracy, dynamic response, stability, robustness, and computational efficiency. This section synthesizes the most frequently reported metrics and discusses their implications for comparative evaluation. Key Metrics Identified Across Studies:

- Root Mean Square Error (RMSE): Reported in 67% of studies, RMSE was the dominant metric for quantifying trajectory tracking accuracy. Its prevalence underscores the central role of precision in manipulator applications;
- Settling Time: Documented in 43% of studies, this metric evaluates transient response and is especially critical in high-speed or repetitive tasks;
- Overshoot: Observed in 31% of papers, overshoot reflects control stability and is particularly significant in domains such as medical or cooperative robotics, where safety and precision are paramount;
- Control Effort / Energy Consumption: Reported in 26% of studies, this metric provides insights into actuator efficiency and long-term sustainability, yet remains underutilized despite its importance in mobile and industrial applications;
- Robustness and Noise Rejection: Commonly described qualitatively, robustness reflects resilience to modeling errors, parameter variations, and external disturbances. The lack of standardized quantitative measures remains a limitation;
- Computation Time / Real-Time Feasibility: Explicitly reported in fewer than 20% of studies, this omission highlights a critical gap, as real-time implementation is essential for practical robotic systems.

Observations and Critical Insights:

- The dominance of RMSE and settling time indicates a strong emphasis on accuracy and speed, but the absence of standardized benchmarks reduces the comparability of results across studies;
- Hybrid controllers consistently demonstrated improved RMSE values and shorter settling times

compared to standalone methods, suggesting that methodological integration enhances both accuracy and responsiveness;

- Very few studies reported on computational cost or control effort, limiting the assessment of real-time feasibility and hardware efficiency. This gap highlights the need for future work to systematically integrate these underreported metrics to strengthen claims of practical applicability.

3.6. Quality Assessment Results

As described in Section 2.6, each of the 80 included studies was evaluated using a structured quality assessment rubric based on four criteria: clarity of control methodology, experimental validation, completeness of reported results, and relevance to rigid link manipulators (RLMs). The studies were then classified into three quality categories: high, moderate, and low, as summarized in Table 4. The distribution of studies across these categories is as follows:

- High Quality (Score 7–8): 27 studies (33.8%).
- Moderate Quality (Score 5–6): 35 studies (43.8%).
- Low Quality (Score ≤4): 18 studies (22.5%).

A pie chart in Fig. 6. was generated to visually illustrate the proportion of studies in each quality tier, providing a clear overview of methodological rigor across the reviewed literature.

These results indicate that while a substantial portion of the literature demonstrates methodological rigor, a majority of studies still fall into the moderate or low-quality range. The most common shortcomings observed in lower-scoring studies included:

- Lack of experimental validation (simulation-only);
- Incomplete performance metric reporting;
- Absence of baseline comparisons or real-time analysis.

Conversely, high-quality studies tended to provide well-formulated control algorithms, validated results on physical robotic systems, and complete quantitative reporting. These studies were also more likely to propose hybrid approaches or integrate learning-based components.

For instance, study [42] was rated as high quality due to its use of deep reinforcement learning, experimental validation, and comprehensive metric analysis including real-time performance. Furthermore, the quality classification was not merely descriptive, but served as a weighting factor in the overall synthesis. Specifically, greater emphasis was placed on conclusions drawn from high-quality studies in trend analysis, performance comparisons, and thematic mapping. This approach helped reduce the influence of biased or incomplete studies on the final insights. Additionally, an informal cross-tabulation indicated that high-quality studies were more frequently associated with application domains such as real-time control and precision robotics, suggesting a link between research depth and practical implementation focus. This quality assessment provided a robust foundation for the subsequent risk of bias and gap analyses, ensuring that the review's conclusions reflect both the quantity and reliability of the existing evidence.

3.7. Risk of Bias Summary

In addition to quality assessment, a risk of bias analysis was performed to evaluate the methodological transparency and reporting reliability of the included studies. As explained in Section 2.7, this analysis focused on five qualitative indicators known to influence the credibility of control system research: simulation-only validation, selective reporting, lack of baseline comparison, incomplete data, and limited application scope.

The distribution of these bias indicators across the 80 included studies is summarized in Table 5, with findings outlined:

- Simulation-Only Validation: A total of 52% of studies did not include any experimental validation and relied solely on simulation, raising concerns about real-world applicability.
- Selective Reporting: 41% of studies reported only favorable metrics (e.g., RMSE), omitting others such as control effort, overshoot, or robustness. This limits objective performance comparison.
- Lack of Baseline Comparison: 36% of studies failed to benchmark their proposed approach against conventional methods (e.g., PID or SMC), reducing the interpretability of performance claims.
- Incomplete Data Reporting: Around 26% of the studies did not provide complete quantitative results, making replication or validation difficult.
- Limited Application Scope: 15% of the papers tested their methods only in narrow or idealized scenarios, without addressing realistic tasks or disturbances.

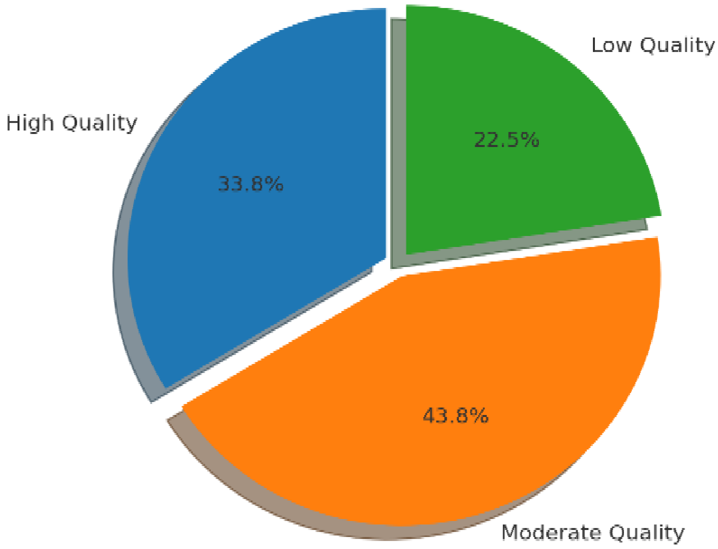

Fig. 6. Quality classification distribution of the 80 included studies

A visual summary of the distribution of these bias indicators is presented in Fig. 7., providing a quick comparative overview of how frequently each issue occurred across the reviewed literature.

These findings highlight common weaknesses that may undermine the generalizability or credibility of the results. While several high-quality studies addressed all five indicators, a notable portion exhibited moderate to high bias in one or more dimensions.

Notably, a cross-comparison with the quality assessment scores revealed a strong overlap between studies with high bias and those categorized as low quality, further validating the impact of these indicators on the overall credibility of the research.

In particular, the lack of hardware validation and absence of baseline comparisons were the most recurring limitations, especially in studies relying on advanced neural or metaheuristic approaches. Overall, the bias assessment reinforces the need for future research to adopt standardized reporting practices, include experimental validation, and compare performance with well-established control baselines to ensure reproducibility and practical relevance.

3.8. Identified Research Gaps

Through the systematic review and synthesis of 80 studies on intelligent control of rigid link manipulators (RLMs), several recurring research gaps and limitations have been identified. These gaps hinder the full deployment of intelligent controllers in real-world robotic systems and highlight key directions for future investigation. These findings are summarized in Table 7.

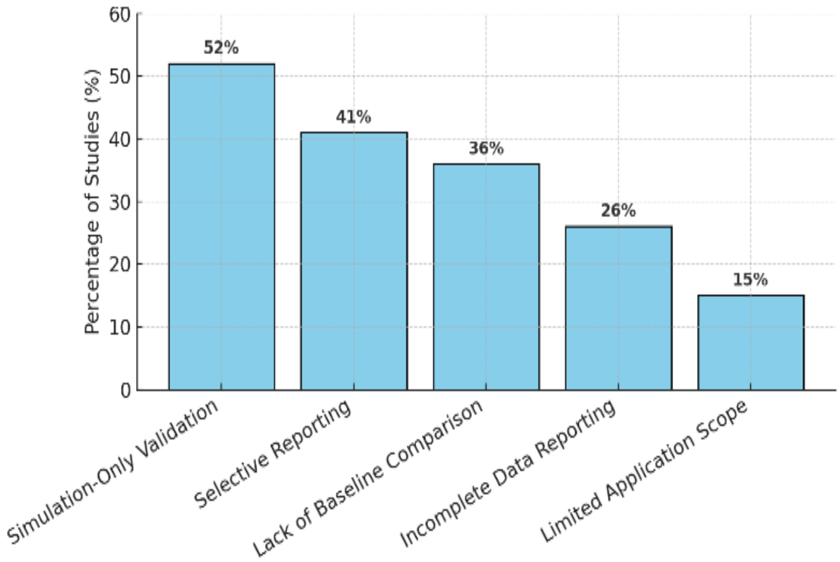

Fig. 7. Distribution of risk of bias indicators across reviewed studies

Table 7. Comparative summary of 25 key studies on intelligent control of RLMs

Research Gap	Description	Representative Studies
Limited Experimental Validation	Despite the proliferation of intelligent control methods, over half of the studies relied solely on simulation without hardware testing. This raises concerns about real-world applicability, particularly in environments involving uncertainty, noise, or physical constraints. Addressing this is essential for practical deployment.	[5], [61], [8], [62], [63]
Incomplete Performance Reporting	Many studies reported only RMSE or trajectory accuracy, neglecting critical performance dimensions such as control effort, robustness under disturbances, or execution time. This lack of standardized and complete reporting makes objective comparison and benchmarking difficult. Future work should adopt a more comprehensive evaluation.	[64], [53], [61], [27]
Lack of Comparative Analysis	A significant number of studies did not compare their methods to conventional baselines (e.g., PID, SMC), making it difficult to assess relative advantages or trade-offs. Without such comparisons, novel approaches risk overstating their contributions. Benchmark-based validation is needed.	[11], [55], [65]-[67], [44]
Underexplored Use of Learning-Based and Hybrid Techniques	While interest in hybrid (e.g., ANN+FLC) and learning-based (e.g., RL) methods is growing, their implementation remains limited in experimental settings, due to concerns over computational cost, training time, and safety. These approaches warrant further hardware validation and optimization for real-time use.	[58], [59], [68], [69]
Absence of Benchmark Tasks or Datasets	The field lacks standardized benchmark scenarios or datasets for evaluating intelligent controllers on RLMs. This creates fragmentation and reduces the reproducibility of results across different research groups. Collaborative benchmarking efforts are needed.	[49], [14]
Scarce Attention to Explainability and Safety	Few studies addressed explainable AI (XAI) in control decisions or integrated safety-aware mechanisms, which are essential for industrial, surgical, or collaborative applications. Integrating explainability and safety constraints is critical in safety-critical environments.	[70]-[72]

Collectively, these gaps point to a need for more rigorous, standardized, and experimental research—particularly in real-time applications where safety, adaptability, and interpretability are

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critical. Addressing these challenges will be essential for transitioning intelligent control methods from theory to practice in robotic manipulators.

4. Discussion

The findings of this systematic review provide important insights into the evolution, current state, and limitations of intelligent control techniques applied to rigid link manipulators (RLMs). By analyzing 80 peer-reviewed studies published between 2016 and 2024, several trends and critical observations emerge that inform both theory and practice.

4.1. Shifts in Control Strategy Preferences

A clear trend was observed in the transition from classical control strategies—such as PID and SMC—towards more adaptive and learning-based techniques like FLC, ANN, and RL. This shift reflects the increasing need for robustness and flexibility in handling nonlinear dynamics and unmodeled disturbances [4], [23], [73], [74]. This transition also aligns with broader advancements in AI and the growing demand for flexible robotic systems capable of operating in unstructured or dynamic environments. Despite this evolution, the continued reliance on PID and SMC (used in over 25% of reviewed studies) indicates their practical appeal in terms of simplicity and real-time feasibility, especially in industrial settings [30].

4.2. The Promise and Pitfalls of Hybrid Control

Hybrid controllers (e.g., ANN-FLC, RL-GA) were shown to outperform individual methods in simulation environments by combining the strengths of different paradigms [75]-[77]. However, their limited real-world deployment, due to complexity and computational burden, underscores the need for optimization and hardware-oriented adaptation [78], [68]. For example, recent studies [59], [69] have begun to explore real-time RL-FLC implementations, suggesting the feasibility of such integration with proper tuning. These techniques hold great promise but require deeper integration into experimental platforms to realize their full potential.

4.3. Experimental Validation Remains a Bottleneck

More than 50% of the reviewed studies relied solely on simulation, which limits external validity [15]. Studies that incorporated physical hardware validation often reported discrepancies between simulated and real-world behavior—particularly under fast motion or external perturbations [79]. This gap must be addressed to facilitate trustworthy deployment of intelligent control systems [80]. Future work should prioritize low-cost, reproducible hardware implementation frameworks to facilitate broader experimental testing and result validation.

4.4. Reporting Practices and Benchmarking Deficiencies

The heterogeneity in reporting performance metrics—especially the lack of data on energy consumption, control effort, or execution time—complicates objective comparison across studies [14]. Furthermore, the absence of standardized tasks or benchmark datasets prevents cumulative progress [69], [81]. Introducing open-source benchmark scenarios (e.g., Meta-World, OpenAI Gym, ROS-based tasks) could enable fair comparison and accelerate development in the field. Establishing unified reporting protocols would enhance reproducibility and comparability in the field.

4.5. Implications for Research and Industry

For researchers, the findings highlight several unexplored opportunities: applying reinforcement learning in hardware [82], integrating explainability in AI-based control [83], and designing benchmark-driven evaluations [84]. For practitioners, the analysis shows that while classical controllers remain viable, intelligent and hybrid strategies offer performance gains if tailored to hardware constraints [85], [86]. Collaboration between academia and industry is essential to ensure the safe and certified deployment of intelligent control in mission-critical robotic systems.

Overall, the current body of literature demonstrates significant theoretical innovation but is still maturing in terms of practical deployment, standardization, and reproducibility. Closing this gap is essential to enabling intelligent control systems that are not only high-performing but also safe, reliable, and deployable in real-world robotic applications, particularly in safety-critical domains such as collaborative robots, surgical systems, and autonomous manufacturing [87]-[94].

5. Conclusions and Future Work

This systematic review analyzed a total of 80 peer-reviewed studies published between 2016 and 2024 on the application of intelligent control strategies to rigid link manipulators (RLMs). The study revealed a notable shift from conventional controllers-such as PID and SMC-toward more adaptive, hybrid, and learning-based approaches, including fuzzy logic control (FLC), artificial neural networks (ANN), and reinforcement learning (RL). While these intelligent methods offer promising improvements in robustness, precision, and adaptability, their widespread deployment in real-world systems remains limited due to simulation-only validation, computational demands, and non-standardized performance reporting.

The quality assessment showed that only 33.8% of the studies met high methodological standards, while over half lacked experimental validation. In addition, the risk of bias analysis further underscored common weaknesses such as selective reporting and absence of baseline comparisons. These findings highlight a need for more rigorous design, reproducibility, and real-time evaluation in future work. Based on these findings, the following research directions are recommended to advance the field:

- Real-Time Hardware Validation: Future work should focus on deploying learning-based controllers on physical robots, incorporating safe and efficient training strategies to bridge the simulation-to-reality gap.
- Explainable AI (XAI): Incorporating interpretability into control logic is critical for trust, debugging, and human–robot interaction in safety-critical systems.
- Standardized Benchmarks and Datasets: Community-wide efforts are needed to define benchmark tasks, shared datasets, and unified reporting protocols for performance metrics.
- Energy-Aware and Multi-Objective Control: Optimizing for both performance and energy efficiency is still underexplored and essential for mobile and embedded robotic platforms.
- Context-Aware Hybrid Controllers: Future systems should dynamically switch or blend control modes based on task type, environmental uncertainty, or system state.
- Safety and Fault Resilience: Emphasizing collision avoidance, safe learning, and robust fault recovery mechanisms is essential for real-world deployment, particularly in unstructured or human-centric environments.

In conclusion, while the field of intelligent control for RLMs is advancing rapidly in algorithmic development, it remains in the early stages of practical maturity. Addressing the identified challenges will pave the way for robust, interpretable, and real-time control systems applicable to advanced robotics across industrial, medical, and service domains.

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Appendix

No	Abbreviation	Description
1	DOF	Degree of Freedom
2	RLM	Rigid Link Manipulator
3	PID	Proportional–Integral–Derivative
4	FLC	Fuzzy Logic Control
5	ANN	Artificial Neural Network
6	SMC	Sliding Mode Control
7	RL	Reinforcement Learning
8	GA	Genetic Algorithm
9	RMSE	Root Mean Square Error
10	IAE	Integral of Absolute Error
12	PRISMA	Preferred Reporting Items for Systematic Reviews
13	XAI	Explainable Artificial Intelligence
14	AI	Artificial Intelligence
15	ML	Machine Learning
16	X	Cartesian X-coordinate (used in spatial analysis)
17	CPU	Central Processing Unit
18	IEEE	Institute of Electrical and Electronics Engineers
19	MDPI	Multidisciplinary Digital Publishing Institute

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